Physics Informed Residual Neural Network for DeepLense Evaluation Test

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Abstract. This technical report presents a solution for the Machine Learning for Science (ML4Sci) Google Summer of Code (GSoC) 2025 DeepLense evaluation tasks. For Task 1, a standard ResNet-18 is implemented to classify dark matter substructures, achieving 91% validation accuracy at 150 epochs. For Task 2, a Physics-Informed ResNet-18 (PI-ResNet-18) is developed by integrating a gravitational lensing block into the classification pipeline. Physics blocks are optimized for GPU acceleration using PyTorch. Additionally, gradient preprocessing is experimented. Results demonstrate improved classification accuracy and quicker convergence of PI-ResNet-18 compared to the base ResNet-18 model. The notebooks are available at `https://github.com/bsyh/DeepLense`.

1 Statement of Interest

I am a full-time software developer in Canada and a prospective M.S. robotics student at Johns Hopkins University starting in September. I have worked as a research assistant in robotics and cognitive classification, and as a robotics engineer intern. Supervised learning has been widely explored in image classification. However, some architectures may lack interpretability in physics-driven domains like gravitational lensing [3] and robot dynamics due to their black-box nature. I am interested in physics-integrated models that constrain learning in a rule-based way and am eager to explore the reliability and efficiency of this approach. With time available in the summer before graduate school, I seek an opportunity to commit to the Physics Guided Machine Learning project and maintain it long-term.

2 Solution

2.1 Task 1: Standard ResNet-18

I implemented a Residual Neural Network (ResNet-18) to classify dark matter substructures, leveraging its ability to maintain high-resolution information through skip connections. ResNet-18 achieved the highest AUC among eight architectures in a prior substructure classifier performance analysis [1].

2.2 Task 2: Physics-Informed ResNet-18

For Task 2, I developed a Physics-Informed ResNet-18 (PI-ResNet-18) by incorporating gravitational lensing equations into the classification pipeline, utilizing the Physics Blocks from LensPINN [2]. The physics block computes the inverse source image from the observed lensing image using the gravitational lensing equation, specifically by solving the lens equation. This block is migrated to PyTorch for batch-wise GPU-accelerated computation. The resulting two-channel input, original lensing image and its inverse source image, is fed into ResNet-18, with the first convolutional layer modified to accept two channels instead of one. Additionally, I experiment with PI-ResNet-18 with gradient preprocessed images as the third channel. The result will be denoted as PI-ResNet-18-Preprocessed.

3 Experiments

3.1 Dataset

Table 1. Dataset sizes used for training and evaluation of the ResNet-18, PI-ResNet-18, and PI-ResNet-18-Preprocessed models. The full training dataset is split 9:1 into training and test sets, while the validation dataset is reserved for evaluation only.

Dataset Split	**Size**
Full Training Dataset	30,000
Training Split	27,000
Test Split	3,000
Validation Dataset	7,500

For data augmentation, the training split was operated by random rotations of 90°, 180°, and 270°. The validation data remains unchanged.

3.2 Trainer

Table 2. Shared training configuration for all three models.

Component	**Configuration**
Loss Function	Cross-Entropy Loss (`nn.CrossEntropyLoss`)
Optimizer	AdamW (`torch.optim.AdamW`, $lr = 6 \times 10^{-3}$)
Learning Rate Scheduler	ReduceLROnPlateau (min mode, patience=10, factor=0.5)

3.3 Results

The performance of the models was evaluated using the Area Under the Curve (AUC) metric across three datasets: ’no’, ’sphere’, and ’vort’. Table 3 and Figure 1 summarizes the AUC scores for each model.

Table 3. AUC scores for ResNet-18, PI-ResNet-18, and PI-ResNet-18-Preprocessed across the ’no’, ’sphere’, and ’vort’ datasets.

Model	**AUC (no)**	**AUC (sphere)**	**AUC (vort)**
ResNet-18	0.98860	0.68420	0.98511
PI-ResNet-18	0.99206	0.97997	0.99270
PI-ResNet-18-Preprocessed	0.97706	0.95757	0.96059

Table 3 demonstrate that PI-ResNet-18 outperforms the standard ResNet-18, particularly on the ’sphere’ dataset, where the AUC improves from 0.68420 to 0.97997. This improvement is attributed to the incorporation of physics-informed features, which provide additional context about gravitational lensing effects. The PI-ResNet-18-Preprocessed model also shows strong performance but slightly under PI-ResNet-18, possibly due to insufficient training time. Because an third channel does not influence the information of the other two channels. Figure 1 presents the ROC curves for the three models, illustrating PI-ResNet-18’s best classification capability. Figure 2 shows the validation loss over 150 epochs, revealing that physics-informed models converge earlier than the base model.

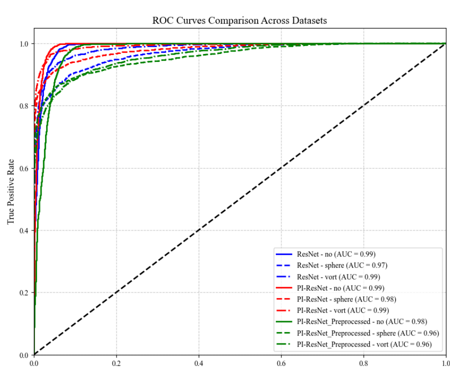

Fig. 1. ROC curves and AUC

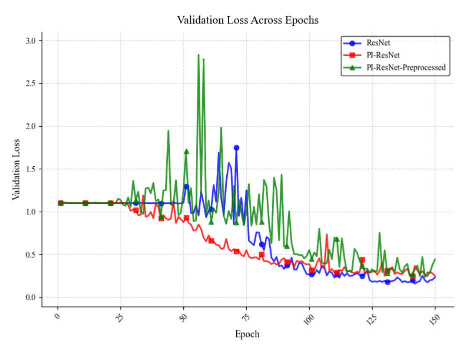

Fig. 2. Validation loss across epochs 0–150 for the three models.

References

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